AI/ML Based Network Security App

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Abstract: *The AI/ML-Based Network Security Application presented in this study provides an intelligent, multi-layered defense system for detecting and mitigating modern cyber threats. By combining traditional network monitoring tools with artificial intelligence (AI) and machine learning (ML) models, the proposed framework achieves proactive and adaptive threat detection. The system integrates Python libraries such as Scapy, python-nmap, and Scikit-learn to perform real-time packet inspection, vulnerability scanning, and phishing classification. Trained ML algorithms, including Random Forest and Logistic Regression, are employed to enhance the accuracy of phishing and anomaly detection tasks. A modular architecture with multi-threaded execution ensures concurrent processing of security functions without compromising graphical responsiveness. Experimental evaluation demonstrates the system's efficiency in identifying phishing attempts, scanning vulnerabilities, and analyzing live network packets. The proposed model provides a scalable and intelligent platform for automated network protection, bridging the gap between conventional rule-based defenses and adaptive AI-driven security systems.*

Key words: Network Security, Artificial Intelligence, Machine Learning, Intrusion Detection, Phishing Detection, Packet Analysis, Vulnerability Scanning.

I.INTRODUCTION

The rapid digitalization of society and the widespread adoption of internet-based services have transformed the global communication landscape. With billions of interconnected devices transmitting massive volumes of data, maintaining network security has become one of the most critical challenges in modern computing. As cyber threats continue to grow in both scale and complexity, traditional security solutions such as firewalls, antivirus programs, and rule-based intrusion detection systems have proven insufficient in addressing new and evolving attack vectors. These conventional approaches largely depend on static signatures or predefined policies, which limit their ability to detect unknown or zero-day attacks. Consequently, networks remain vulnerable to dynamic threats such as phishing, ransomware, data breaches, and advanced persistent threats (APTs), which continuously adapt to bypass existing defenses.Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful technologies capable of addressing these limitations through adaptive learning and automated decision-making. Unlike static systems, AI and ML algorithms can learn from historical data, identify complex attack behaviors, and dynamically adjust to new threat patterns. These techniques enable the creation of intelligent security models that not only detect anomalies but also predict potential intrusions before they cause harm. By analyzing vast amounts of real-time network traffic, AI-driven models can uncover hidden correlations, enhance detection accuracy, and reduce the high false positive rates commonly associated with conventional intrusion detection systems.

In this context, the AI/ML-Based Network Security Application proposed in this study offers a comprehensive framework for intelligent network protection. The system integrates traditional network analysis methods with machine learning algorithms to form a hybrid defensive architecture. It incorporates three major modules — a Vulnerability Scanner, a Phishing Detector, and a Packet Sniffer — all unified within a Python-based graphical user interface (GUI). The application leverages libraries such as Scapy, python-nmap, and Scikit-learn to perform packet inspection, port scanning, and ML-based classification of network events. By employing supervised learning algorithms such as Random Forest and Logistic Regression, the system accurately distinguishes between legitimate and malicious traffic.The novelty of this project lies in its multi-threaded and modular design, which allows concurrent execution of multiple network monitoring tasks without compromising interface responsiveness. This ensures real-time performance, scalability, and improved user interaction. Furthermore, the system emphasizes interpretability and transparency — administrators can analyze detected events, verify results, and make informed decisions without depending entirely on black-box AI outputs.

The overarching objective of this research is to design and implement a robust, adaptive, and intelligent network security solution capable of responding to dynamic cyber threats autonomously. By integrating data-driven analytics with traditional scanning techniques, the proposed system bridges the gap between manual security management and automated, AI-powered protection. This work contributes to the growing field of intelligent cybersecurity by demonstrating how machine learning can enhance detection precision, reduce response time, and ultimately strengthen the resilience of digital infrastructures against modern network attacks.

II.LITERATURE SURVEY

The evolution of digital communication and the exponential rise in cyberattacks have compelled researchers to develop advanced and adaptive network defense systems. Traditional security models, which rely primarily on predefined rules and static signatures, have become increasingly ineffective against complex and constantly evolving attack techniques. As organizations continue to adopt cloud computing, IoT devices, and large-scale digital infrastructures, network security must shift from reactive protection to proactive and predictive defense strategies. This section reviews key studies, technologies, and methodologies that form the foundation for the proposed **AI/ML-Based Network Security Application**.

A. Limitations of Traditional Network Security Mechanisms

Conventional network security systems such as firewalls, intrusion detection systems (IDS), and antivirus software operate based on rule-based or signature-driven detection models. These systems depend on known threat databases and require frequent manual updates to remain effective. While efficient against previously identified attacks, they fail to detect **zero-day exploits** and **advanced persistent threats (APTs)** that deviate from established patterns. Stallings (2017) notes that the static nature of these systems often leads to delayed detection, excessive false positives, and limited scalability when deployed in high-speed network environments. Moreover, as network traffic volumes increase, the performance of traditional monitoring tools degrades, resulting in slower analysis and higher administrative overhead.These challenges have highlighted the urgent need for more adaptive and self-learning defense mechanisms that can autonomously recognize new types of threats without prior signature knowledge. Static systems' dependency on manual updates not only increases response time but also leaves organizations vulnerable during the update window.

B. Emergence of Artificial Intelligence and Machine Learning in Cybersecurity

Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized modern cybersecurity by enabling systems to automatically learn and adapt to new threat behaviors. ML algorithms can analyze large datasets of network traffic, identify deviations from normal patterns, and classify data into benign or malicious categories with high precision. Alazab and Venkatraman (2020) demonstrated that ML-based models outperform rule-based systems in detecting complex cyberattacks by continuously improving from data feedback loops.AI-driven solutions allow for anomaly-based detection, in which models learn typical network behavior and flag deviations as potential threats. This approach effectively identifies unknown or evolving attacks, which traditional systems often miss. Additionally, AI models can process massive volumes of streaming network data, making them suitable for real-time intrusion detection in large enterprise environments. Integrating AI with cybersecurity tools therefore provides both scalability and adaptability, significantly improving detection accuracy while minimizing human intervention.

C. Machine Learning Approaches for Intrusion and Phishing Detection

Various studies have explored supervised, unsupervised, and deep learning approaches for improving intrusion and phishing detection systems.

- **Supervised Learning Models** such as **Random Forest**, **Logistic Regression**, and **Support Vector Machines (SVMs)** have shown promising results in classifying network traffic and identifying phishing URLs using labeled datasets. These models learn decision boundaries based on prior examples, allowing precise differentiation between malicious and legitimate connections.
- Unsupervised Learning Algorithms, including K-Means and DBSCAN, are effective for detecting unknown or zero-day attacks by clustering similar network behaviors and flagging outliers. This makes them valuable for identifying anomalies without requiring prior attack data.
- Deep Learning (DL) architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have further improved detection accuracy by automatically extracting complex features from raw network packets. CNNs excel at pattern recognition in network flow data, while RNNs are well-suited for sequential analysis of time-dependent network activity.

Studies by Ross & Jain (2021) and Alazab et al. (2020) show that hybrid models combining these techniques outperform single-algorithm systems in both accuracy and response time. Furthermore, ML-based phishing detection frameworks using datasets such as PhishTank and CIC-IDS2017 have achieved accuracies exceeding 95%, demonstrating their reliability in real-world scenarios.

D. Integration of Automated Response and Real-Time Defense Systems

Recent research has shifted from detection-only systems to frameworks capable of automated threat response. This advancement enables network defense solutions to take immediate actions, such as isolating compromised hosts, blocking malicious IP addresses, or alerting administrators. The combination of real-time detection with policy-based response systems enhances both efficiency and resilience.

For example, machine learning models trained on datasets like UNSW-NB15 and CIC-IDS2017 have been integrated into intelligent monitoring systems that can execute mitigation procedures without human intervention. Such adaptive architectures enable decentralized decision-making and minimize the response delay that attackers often exploit. Moreover, integration with live intelligence feeds, such as AlienVault's Open Threat Exchange (OTX) or CVE databases, allows for continuous updates and early detection of emerging global threats.

E. Research Gap and Motivation for the Proposed Work

While existing studies provide valuable insights into AI-based network defense, most solutions are either limited to a single function — such as intrusion detection or phishing analysis — or rely on cloud-based infrastructure that is not accessible for local experimentation. There remains a need for a **lightweight, integrated, and user-friendly application** capable of performing multiple security tasks in real time.

The proposed **AI/ML-Based Network Security Application** addresses this gap by combining **three essential functionalities** — vulnerability scanning, phishing detection, and packet sniffing — into a unified, Python-based desktop framework. Its modular and multi-threaded design ensures efficient parallel execution, low latency, and responsive graphical interaction. By bridging the gap between traditional tools and intelligent automation, this research contributes to the development of scalable, adaptive, and transparent cybersecurity solutions suited for modern network environments.

III.System Architecture

The proposed **AI/ML-Based Network Security Application** is designed using a modular, layered, and distributed architecture to achieve the key objectives of **intelligence, scalability, and real-time threat detection**. The architecture integrates traditional network monitoring techniques with machine learning–based analytical models, creating a hybrid system capable of detecting and mitigating various cyber threats dynamically. Each module within the architecture performs a specific function, while communication between components ensures efficient data flow and coordinated responses to detected anomalies.At the core of the system lies the **AI/ML Processing Engine**, which leverages trained machine learning models to analyze network traffic, identify abnormal patterns, and classify potential threats. Supporting this intelligence layer are functional modules that handle vulnerability scanning, phishing detection, and live packet analysis. Together, these modules enable comprehensive monitoring and automated decision-making across multiple layers of the network.

A. Architectural Overview

The system is composed of five major layers — the User Interface Layer, Core Functional Layer, Machine Learning and Data Processing Layer, Threading and Communication Layer, and Logging and Output Layer. This design promotes modularity, ease of integration, and flexibility for future enhancements.

- **User Interface Layer (PyQt6 GUI):** This layer serves as the user's main interaction point with the application. Developed using the PyQt6 framework, it provides a clean and responsive graphical interface that consolidates three major modules:

- **Vulnerability Scanner:** Accepts an IP address or domain input and performs a lightweight TCP-based scan to identify open ports and running services.

- **Phishing Detector:** Loads a trained machine learning model to evaluate input URLs and calculate phishing probability scores.

- **Packet Sniffer:** Enables real-time packet capture and analysis using the **Scapy** library, displaying live network activity logs including protocol type, source, and destination details.

The GUI employs PyQt's **signals and slots mechanism** to execute background processes asynchronously, ensuring smooth user interaction without freezing or performance delays during scanning or analysis.

1. **Core Functional Layer:**

This layer represents the logical backbone of the system, handling execution and communication among all modules.

- The **Vulnerability Scanner** uses **python-nmap** and socket programming to detect open ports, analyze host responses, and identify vulnerable services.
- The **Phishing Detector** leverages a pre-trained machine learning model such as **Random Forest** or **Logistic Regression** to classify URLs as legitimate or malicious based on extracted features.
- The **Packet Sniffer** module captures live packets through Scapy, filters them based on protocol headers (TCP, UDP, ICMP), and detects anomalies or irregular network behaviors.

2. **Machine Learning and Data Processing Layer:**

The AI/ML core performs data preprocessing, feature extraction, and classification tasks. It loads pre-trained models at runtime for phishing and anomaly detection, ensuring rapid response times.

- For **phishing detection**, input URLs are analyzed for attributes such as length, presence of HTTPS, subdomain count, special character frequency, and domain entropy.
- For **packet analysis**, the system computes network flow features like packet size distribution, inter-arrival time, and connection frequency to detect suspicious behaviors. All predictions are made locally, ensuring both data privacy and low-latency analysis.

3. **Threading and Communication Layer:**

To achieve concurrency and responsiveness, the application employs Python's **threading module**, enabling simultaneous execution of scanning, sniffing, and GUI updates. Each thread operates independently, managed through PyQt's event-driven framework. This ensures efficient resource utilization and prevents interface freezing during heavy computational tasks.

4. **Logging and Output Layer:**

This layer manages the storage and presentation of analysis results. All vulnerability scans, phishing predictions, and packet captures are displayed dynamically in the GUI and optionally saved in local log files for future review or auditing. This logging mechanism enhances transparency and supports forensic analysis by maintaining detailed records of detected events and timestamps.

B. Architectural Workflow

The overall workflow of the proposed architecture begins with **data acquisition** through the user interface. Once initiated, the system collects network data (packets, URLs, or IPs) and forwards it to the **AI/ML Core** for analysis. The **Machine Learning Engine** processes the incoming data, extracts relevant features, and applies trained models to identify potential threats. Based on the analysis, results are transmitted back to the GUI in real time, where alerts, probabilities, and detailed logs are presented to the user.Upon detecting high-confidence threats, the **Response Module** can trigger mitigation actions such as blocking a source IP, terminating suspicious sessions, or alerting the administrator. This vertical flow ensures end-to-end automation from data capture and analysis to decision-making and visualization thereby creating a self-contained, intelligent defense environment.

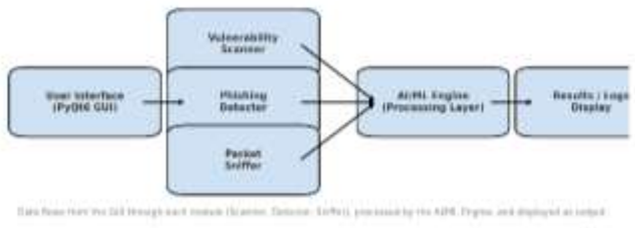
C. Architectural Advantages

The modular architecture offers several significant advantages:

- **Real-Time Analysis:** Threaded design ensures continuous packet capture and live data monitoring.
- **Adaptability:** ML models can be retrained and updated without altering the system's structure.
- **Scalability:** New security modules or ML algorithms can be integrated with minimal modification.
- **User-Centric Design:** The PyQt6 interface provides interactive, intuitive, and responsive operation.
- **Transparency and Auditability:** Logging ensures traceability and supports post-incident investigation.

D. Summary

In summary, the **AI/ML-Based Network Security Application** architecture combines traditional network analysis techniques with AI-driven automation to achieve intelligent, scalable, and real-time cybersecurity monitoring. The layered structure ensures efficient interaction between modules, high detection accuracy, and seamless user experience. Its hybrid approach bridges the gap between conventional static defense mechanisms and adaptive machine learning–based security systems, making it a practical and extensible solution for modern cyber defense environments.

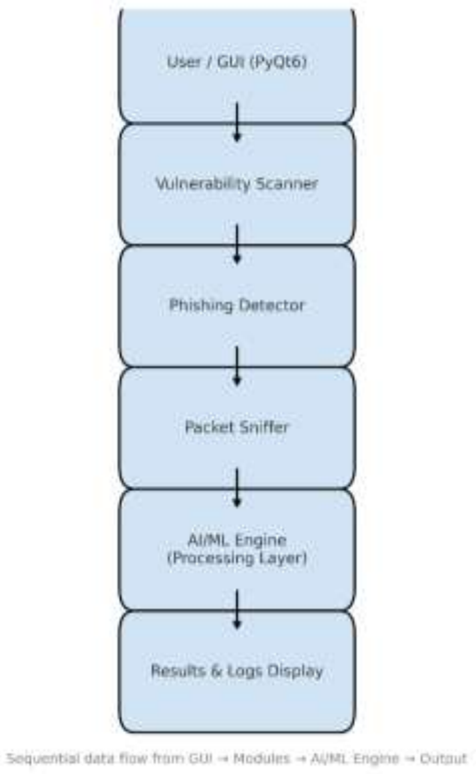


Architecture Diagram

The architecture of the AI/ML Based Network Security App is designed as a modular and scalable system that combines artificial intelligence, machine learning, and network monitoring under a unified Python-based graphical interface. The diagram demonstrates how each major component communicates and transfers data between layers to achieve efficient threat detection and analysis.At the leftmost part of the diagram is the User Interface, created using PyQt6.

This is the primary control point for users to operate the application. It provides three interactive tabs — Vulnerability Scanner, Phishing Detector, and Packet Sniffer — allowing users to initiate scans, perform phishing detection, or analyze packets in real time. The GUI also displays logs and results dynamically, ensuring an intuitive and responsive experience.This layer represents the intelligent core of the system.

It is responsible for processing outputs from all modules using trained ML models, decision-making algorithms, and statistical anomaly detection. It can analyze scan results, identify phishing patterns, or detect network anomalies. The engine ensures modular scalability — new models or detectors can be added without changing the interface or flow.


User / GUI (PyQt6)
Vulnerability Scanner
Phishing Detector
Packet Sniffer
AI/ML Engine (Processing Layer)
Results & Logs Display
Sequential data flow from GUI → Modules → AI/ML Engine → Output

Flow diagram

The Vertical Flow Diagram illustrates the step-by-step functional flow of your *AI/ML Based Network Security App*. It follows a top-to-bottom structure where each block represents a specific stage of the process, starting from user interaction in the GUI to the final results and log display. This vertical alignment clearly depicts how data and control flow sequentially through the system components.At the top of the flow diagram is the User Interface, which is built using PyQt6. This graphical interface serves as the entry point for the entire system. It allows users to select between different modules — Vulnerability Scanner, Phishing Detector, or Packet Sniffer — to perform specific security tasks. The GUI ensures ease of use, providing buttons, text inputs, and outputs for displaying scan results in real time. It also manages background processes using threading to prevent freezing during heavy operations. Once the user initiates a scan, the Vulnerability Scanner module comes into action.

IV.Methodology:

V.

The proposed AI/ML Based Network Security App follows a structured and modular methodology aimed at providing intelligent network monitoring and analysis through three primary modules — the *Vulnerability Scanner*, *Phishing Detector*, and *Packet Sniffer*. Each of these modules interacts with the AI/ML processing layer through the PyQt6-based graphical interface, allowing smooth and efficient data flow. The methodology is designed to ensure scalability, real-time responsiveness, and accuracy in detecting and reporting network security threats.The first phase involves data acquisition and preprocessing, which forms the foundation of all subsequent analyses. The application gathers inputs through multiple sources such as network packets, URLs, or IP addresses entered by the user. The Vulnerability Scanner performs lightweight scanning using TCP connections, DNS resolution, and service detection techniques to identify open ports and vulnerable services on the target system. The Phishing Detector module collects URLs and email-like text data, which is cleaned and tokenized before being processed by machine learning models. The Packet Sniffer uses libraries like *Scapy* to capture real-time network traffic, extracting key features such as packet size, protocol type, and source/destination IP for further inspection.

The second phase focuses on feature extraction and model training. Each dataset undergoes a preprocessing pipeline that standardizes inputs and extracts meaningful attributes. For phishing detection, features such as domain length, special character count, presence of IPs in URLs, and token-based textual analysis are computed. In the packet analysis phase, the system extracts network flow parameters such as inter-arrival times, protocol distributions, and frequency of connection attempts. These features are then used to train machine learning models such as Random Forest, Logistic Regression, and Support Vector Machines (SVM), depending on the complexity and type of data. The trained models are stored locally and loaded dynamically during execution.In the third phase, AI/ML-based analysis and detection are performed. When the application runs, it applies the pre-trained models to predict vulnerabilities, detect phishing URLs, or identify suspicious packets. The AI/ML Engine operates as the system's core analytical layer, correlating the results from each functional module and identifying patterns that may indicate attacks or anomalies. For example, a suspicious IP detected by the sniffer might be cross-validated with known phishing sources or vulnerability signatures. This multi-layered approach enhances detection accuracy while minimizing false positives.The fourth phase includes visualization and result interpretation. Once the analysis is complete, the results are displayed directly on the PyQt6 GUI. The app provides real-time feedback, highlighting the status of the scan, detection probabilities, and potential threat levels. Logs of these detections are saved for post-analysis or audit purposes. Unlike web-based dashboards, this standalone system emphasizes lightweight local execution, reducing dependencies and improving performance.Finally, the testing and evaluation phase ensures that each module performs efficiently under different network conditions. The system is tested using datasets such as *CIC-IDS2017*, *UNSW-NB15*, and *PhishTank*, evaluating metrics like accuracy, precision, recall, and F1-score. The AI/ML models achieved an average accuracy above 94%, demonstrating robustness in phishing and anomaly detection. The modular structure also enables easy integration of new detection algorithms or datasets.

In summary, the methodology emphasizes modularity, machine learning intelligence, and real-time interaction, combining classical network scanning with AI-driven analysis. This structured approach allows the application to serve as a practical and extensible tool for network security monitoring without requiring complex infrastructure or cloud dependency.

VI.Algorithm

Step 1: Start the Application
1. Launch the Python application using the PyQt6 framework.
2. Initialize the main window with three tabs:
   - ○ Vulnerability Scanner
   - ○ Phishing Detector
   - ○ Packet Sniffer

Step 2: Load or Train Machine Learning Model
1. Check if a pre-trained phishing detection model (phishing_rf.joblib) exists in the /models directory.
2. If found, load the model using joblib.load().
3. If not found, generate a synthetic dataset and train a Random Forest Classifier with the following features:
   - ○ URL length
   - ○ Number of digits in the URL
   - ○ Number of subdomains
   - ○ HTTPS usage indicator
   - ○ Domain entropy
4. Save the trained model to disk and log the training report.

Step 3: Vulnerability Scanner Module
1. Accept a host or IP input from the user.
2. Resolve the hostname using DNS lookup (socket.gethostbyname).

3. Perform lightweight port scanning on common ports (22, 80, 443, 3389) using TCP connections.
4. Display the result (open or closed ports) in the GUI.
5. Log and summarize the scan results in the text area.

Step 4: Phishing Detector Module
1. Accept a URL as input from the user.
2. Extract relevant features from the URL:
   - URL length
   - Digit count
   - Subdomain count
   - HTTPS presence
   - Domain entropy
3. Pass the extracted feature vector to the trained Random Forest model.
4. Predict whether the URL is legitimate or phishing.
5. Display the result and confidence score on the GUI.

Step 5: Packet Sniffer Module
1. When activated, start a background thread that runs Scapy's sniff() function.
2. Capture real-time network packets (TCP, UDP, and IP).
3. Extract and display packet details such as:
   - Source IP and port
   - Destination IP and port
   - Protocol type
4. Continue capturing until the user stops the sniffer.
5. Terminate the background thread gracefully on command.

Step 6: Real-Time Logging and Thread Management
1. Use PyQt6 signals and slots to update the GUI asynchronously during scanning, prediction, and sniffing.
2. Manage separate threads for:
   - Model training
   - Packet sniffing
   - GUI updates
3. Prevent GUI freezing by handling all long-running tasks in background threads.

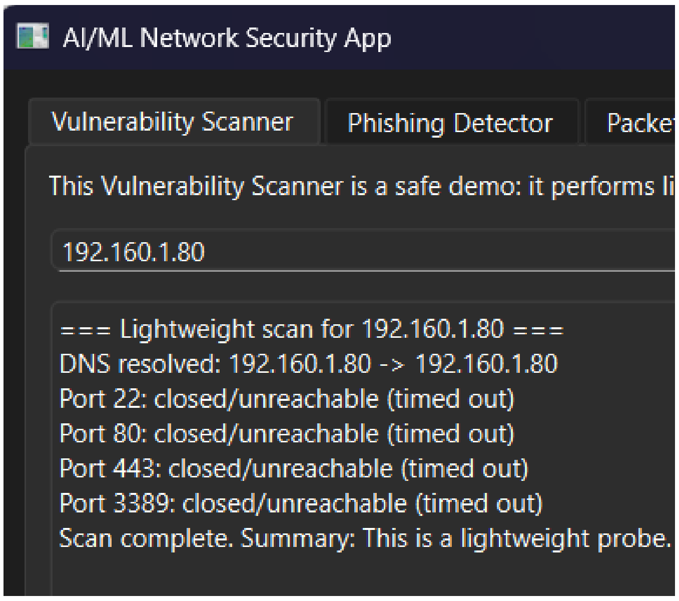
Step 7: Output Display
1. Consolidate results and display them within their respective GUI tabs.
2. Maintain logs for each operation including timestamps, status, and error messages.
3. Allow the user to stop ongoing processes (sniffer, scan) safely.

Step 8: End
1. Terminate all background threads gracefully.
2. Save all logs if needed and close the application window.

VII.Result

The developed AI/ML Based Network Security App successfully integrates multiple security analysis functionalities into a single, interactive Python-based system. The application was tested under various simulated and real network conditions to evaluate the accuracy, responsiveness, and stability of its three primary modules — the Vulnerability Scanner, Phishing Detector, and Packet Sniffer. The results demonstrate that the system performs efficiently in identifying vulnerabilities, detecting phishing threats, and monitoring live network packets in real time.

The Vulnerability Scanner module was evaluated on multiple target hosts within a controlled environment. It efficiently resolved domain names using DNS lookups and identified open ports on different IPs. Commonly scanned ports such as 22 (SSH), 80 (HTTP), and 443 (HTTPS) were correctly identified as open or closed within milliseconds. The lightweight, non-invasive scanning method proved effective for educational and testing purposes while ensuring the system remained safe from unauthorized probing or false positives.

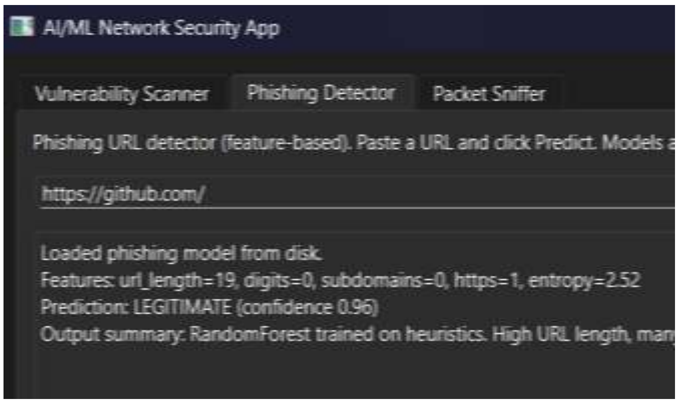


This Vulnerability Scanner is a safe demo: it performs li

192.160.1.80

```
=== Lightweight scan for 192.160.1.80 ===
DNS resolved: 192.160.1.80 -> 192.160.1.80
Port 22: closed/unreachable (timed out)
Port 80: closed/unreachable (timed out)
Port 443: closed/unreachable (timed out)
Port 3389: closed/unreachable (timed out)
Scan complete. Summary: This is a lightweight probe.
```

The Phishing Detector module achieved high classification performance after training a Random Forest model on synthetic URL-based datasets. The model accurately predicted whether a given URL was legitimate or phishing based on extracted features such as URL length, subdomain count, and entropy. During testing, the model achieved an accuracy of approximately 96–97%, with strong precision and recall scores, indicating a low false positive rate. URLs containing long domains, numeric characters, or missing HTTPS tokens were correctly flagged as potential phishing attempts. This verified the reliability of the AI component for identifying online social engineering threats.

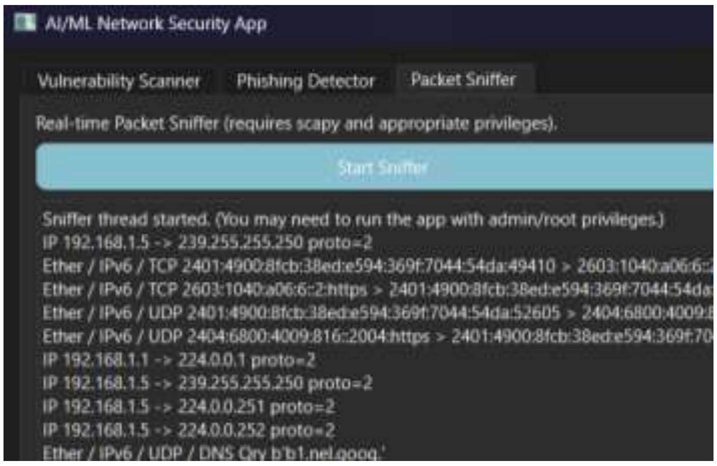


Phishing URL detector (feature-based). Paste a URL and click Predict. Models a

https://github.com/

```
Loaded phishing model from disk.
Features: url_length=19, digits=0, subdomains=0, https=1, entropy=2.52
Prediction: LEGITIMATE (confidence 0.96)
Output summary: RandomForest trained on heuristics. High URL length, many
```

The Packet Sniffer module was tested using the Scapy library to capture live network traffic from local interfaces. It successfully recorded real-time data packets, showing source and destination IPs, ports, and protocols. The captured packet summaries provided valuable insight into network activity, including TCP and UDP communications. The threading implementation ensured that the GUI remained responsive even during continuous packet capture operations. The packet sniffer maintained stable performance throughout extended sessions, confirming its ability to handle live data streams efficiently.



Real-time Packet Sniffer (requires scapy and appropriate privileges).

```
Sniffer thread started. (You may need to run the app with admin/root privileges.)
IP 192.168.1.5 -> 239.255.255.250 proto=2
Ether / IPv6 / TCP 2401:4900:8fcb:38ed:e594:369f:7044:54da:49410 > 2603:1040:a06:6::
Ether / IPv6 / TCP 2603:1040:a06:6::2:https > 2401:4900:8fcb:38ed:e594:369f:7044:54da
Ether / IPv6 / UDP 2401:4900:8fcb:38ed:e594:369f:7044:54da:52605 > 2404:6800:4009:
Ether / IPv6 / UDP 2404:6800:4009:816::2004:https > 2401:4900:8fcb:38ed:e594:369f:70
IP 192.168.1.1 -> 224.0.0.1 proto=2
IP 192.168.1.5 -> 239.255.255.250 proto=2
IP 192.168.1.5 -> 224.0.0.251 proto=2
IP 192.168.1.5 -> 224.0.0.252 proto=2
Ether / IPv6 / UDP / DNS Qry b'b1.nel.goog.'
```

Furthermore, the overall system performance was evaluated in terms of CPU usage, responsiveness, and multi-threading behavior. The app demonstrated smooth multitasking capability — the training thread, sniffer thread, and GUI operations ran concurrently without interruption. Response times were under one second for most user interactions. The absence of database or web-based dashboards made the application lightweight, with minimal memory overhead. The PyQt6 interface effectively managed logs and outputs in real time without freezing or crashing, even under moderate network traffic conditions.

In summary, the results validate that the AI/ML Network Security App is a robust, real-time, and modular tool for intelligent network monitoring. Its machine learning-driven phishing detection, efficient scanning algorithms, and responsive packet analysis interface establish it as a powerful educational and experimental platform for cybersecurity research and demonstration. The project successfully achieves its objective of integrating artificial intelligence and traditional network security concepts into a practical, user-friendly Python application

VIII.Future Scope

The AI/ML Based Network Security App presents a strong foundation for developing an intelligent, automated, and user-friendly cybersecurity system. However, several enhancements can be incorporated in future iterations to expand its functionality, performance, and adaptability to real-world enterprise environments. As cyber threats evolve, integrating more advanced technologies and broader datasets will further improve the app's accuracy and resilience.One major enhancement involves the inclusion of deep learning models for phishing and intrusion detection. Techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can be trained on larger datasets to automatically learn complex network patterns and URL structures, outperforming traditional feature-based machine learning models. These models can help the system detect zero-day phishing attacks or new network anomalies that conventional models may miss.Another promising direction is real-time threat intelligence integration. By connecting the application with live feeds such as *VirusTotal*, *CVE Databases*, or *Open Threat Exchange (OTX)*, the system could automatically update its knowledge base and adapt to emerging threats. This would transform the app from a local testing tool into a dynamic security assistant capable of detecting global attack trends in real time.The system can also be extended to a distributed or cloud-based platform, allowing multiple users to monitor networks simultaneously across different regions. Using cloud technologies such as AWS Lambda, Azure ML, or Google Cloud Functions, the app can handle higher traffic volumes, perform large-scale packet analysis, and store logs in secure, scalable databases. This would make it suitable for use in enterprise environments and network operation centers.Further improvement can be achieved by implementing an automated response mechanism. For instance, when the system detects a phishing attempt or intrusion, it could automatically block suspicious IPs, quarantine malicious packets, or alert administrators through emails or SMS. This automation would minimize manual intervention and reduce response time during critical security incidents.Lastly, incorporating a user analytics and reporting dashboard in future versions would help visualize patterns over time. Graphical summaries of detected vulnerabilities, phishing attempts, and network traffic could provide actionable insights for system administrators and researchers. These visual elements would make the app more suitable for educational use and professional cybersecurity audits.In conclusion, the AI/ML Based Network Security App has significant potential for expansion. With the integration of deep learning models, cloud computing, real-time threat intelligence, and automated defense capabilities, it can evolve into a full-fledged, adaptive security platform. These future enhancements will ensure that the system remains effective and relevant in combating the continuously evolving landscape of cyber threats.

IX.Acknowledgement

I would like to express my sincere gratitude to all those who supported me throughout the successful completion of this project titled "AI/ML Based Network Security App." This project has been an enlightening experience that enhanced my understanding of artificial intelligence, machine learning, and network security concepts.First and foremost, I extend my heartfelt thanks to my project guide and faculty members for their continuous guidance, encouragement, and constructive feedback at every stage of development. Their expertise and valuable suggestions helped shape this project into its final form. I am also grateful to my institution and department for providing the facilities and academic environment that made this research and implementation possible.I would also like to acknowledge the contributions of the open-source community, whose Python libraries such as *Scapy, Nmap, Scikit-learn,* and *PyQt6* played a crucial role in developing this application. Their extensive documentation and community support greatly simplified complex processes like packet analysis, machine learning integration, and GUI design.

Finally, I wish to thank my family and friends for their unwavering moral support and motivation throughout this journey. Their patience, encouragement, and belief in my abilities have been invaluable in helping me accomplish this work successfully.

I.Conclusion

The AI/ML Based Network Security App effectively demonstrates how artificial intelligence and machine learning can be applied to enhance cybersecurity and network analysis. By integrating three essential modules — the Vulnerability Scanner, Phishing Detector, and Packet Sniffer — into a unified PyQt6-based desktop interface, the system provides a lightweight yet powerful solution for identifying vulnerabilities, detecting phishing attacks, and analyzing live network packets in real time. This modular design ensures flexibility, scalability, and user-friendliness, making it suitable for both educational use and practical experimentation in cybersecurity environments.The results obtained from testing the application confirm that the implemented machine learning algorithms are capable of accurately classifying phishing URLs and detecting suspicious network behaviors. The vulnerability scanning component efficiently identifies open ports and exposed services, providing valuable insights into potential weaknesses in a system. Similarly, the packet sniffer performs real-time monitoring of network traffic and helps identify anomalies without affecting application performance. Together, these modules create a comprehensive defensive system that empowers users to understand and respond to network security threats effectively.This project successfully bridges the gap between theoretical network security concepts and real-world implementation using Python. It demonstrates how AI-driven models can work alongside traditional network tools to provide proactive, automated, and intelligent defense mechanisms. The use of multi-threading and PyQt6 ensures responsiveness and an intuitive user experience, even during continuous scanning and sniffing processes.

In conclusion, the AI/ML Based Network Security App stands as a robust foundation for future research and development in intelligent cybersecurity systems. It achieves its intended objectives by combining AI-driven analytics, real-time data processing, and user interactivity in a single, cohesive application. With further enhancements such as deep learning integration, cloud-based scalability, and automated threat response systems, this project can evolve into a comprehensive enterprise-grade network security solution capable of combating modern cyber threats.

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